

An Active Machine Hearing System for Auditory Stream Segregation

Christopher Schymura, Thomas Walther, Dorothea Kolossa

Institute of Communication Acoustics, Ruhr-Universität Bochum, Germany

{christopher.schymura, thomas.walther, dorothea.kolossa}@rub.de

Abstract

This study describes a binaural machine hearing system that is capable of performing auditory stream segregation in scenarios where multiple sound sources are present. The process of stream segregation refers to the capability of human listeners to group acoustic signals into sets of distinct auditory streams, corresponding to individual sound sources. The proposed computational framework mimics this ability via a probabilistic clustering scheme for joint localization and segregation. This scheme is based on mixtures of von Mises distributions to model the angular positions of the sound sources surrounding the listener. The distribution parameters are estimated using block-wise processing of auditory cues extracted from binaural signals. Additionally, the proposed system can conduct rotational head movements to improve localization and stream segregation performance. Evaluation of the system is conducted in scenarios containing multiple simultaneously active speech and non-speech sounds placed at different positions relative to the listener.

Index Terms: computational auditory scene analysis, source separation, source localization

1. Introduction

Human listeners have a remarkable ability to assess complex auditory scenes, even in adverse acoustic conditions. This phenomenon has been thoroughly investigated in the context of auditory scene analysis (ASA), a term that was coined by Bregman [1]. Two essential aspects of ASA are sound source localization and auditory stream segregation, denoting the ability of humans to build a perceptual representation of *where* sounds originate from and *what* kinds of sounds are present in an auditory scene [1, 2, 3]. Human listeners are able to perform this task naturally in a wide range of acoustic conditions, whereas mimicking this capability by computational means still remains very challenging [3]. A wide range of machine hearing systems applied to sound localization and segregation rely on a purely bottom-up information flow, see e.g. [4, 5]. However, various psychophysical studies have shown that the human auditory system incorporates additional top-down knowledge while assessing auditory scenes [2]. This has led to some recent developments in the field of machine hearing, where various models that integrate top-down feedback into their processing path have been proposed [6, 7, 8].

Top-down feedback in machine hearing systems has especially been exploited in the context of binaural localization. Recent studies focus on statistical models [6], deterministic approximations of head related transfer functions (HRTFs) [8] and deep neural networks (DNNs) [7] to map interaural time differences (ITDs) and interaural level differences (ILDs) to the corresponding angular sound directions. By incorporating head movements, these models achieve superior localization perfor-

mance compared to the static case. This arises from their ability to resolve front-back ambiguities, which are likely to occur if sound sources are positioned within the cone of confusion [2]. The results coincide with the psychophysical findings of Wallach [9], which indicate that human listeners also rely on head movements to improve the assessment of sound directions.

This study describes a computational framework which incorporates top-down feedback into the process of auditory stream segregation. Auditory stream segregation is closely related to blind source separation (BSS) techniques from the field of digital signal processing. The task is to segregate binaural signals into distinct *auditory streams*, where each stream corresponds to a specific sound source that is present in the acoustic scene. In contrast to conventional computational models for BSS (see e.g. [10, 11]), the system introduced in this study uses an auditory model [12, 13] for monaural and binaural feature extraction and performs a *dynamic* and active assessment of the auditory scene by incorporating rotational head movements. The segregation process is based on a binaural feature analysis, which yields *soft masks*, similar to many conventional BSS methods. The soft masks are subsequently applied to extracted monaural features which are eventually used to classify the identities of all sound sources present in the scene.

2. System description

The machine hearing system described in this work is composed of different building blocks, dividing the overall process into a sequence of feature extraction, localization, auditory stream segregation, source type identification and feedback initiation. The remainder of this section gives a detailed description of each individual building block.

2.1. Auditory feature extraction

An auditory front-end as proposed in [12] is used to extract monaural and binaural features from binaural ear signals, sampled with a rate of $f_s = 44.1$ kHz. Each channel of the ear signals is decomposed into $L = 64$ auditory channels using a phase compensated gammatone filterbank. The filter center frequencies are equally distributed on the equivalent rectangular bandwidth (ERB) scale between 80 Hz and 8 kHz [3]. Half-wave rectification and low-pass filtering is applied to each frequency channel to approximate the behavior of the inner hair cells (IHCs) [14]. Subsequently, monaural and binaural features are extracted using non-overlapping, rectangularly windowed time frames with a length of 20 ms.

The localization and segregation stage used in this study is based on two primary binaural cues, namely ITDs and ILDs. The ITD between the left and the right ear signal, denoted as τ_{kl} , is estimated for each time frame k and frequency channel l by finding the time lag that corresponds to the maximum of the interaural cross-correlation function. ILDs are estimated anal-

ogously by comparing the frame-based energy of the left and right ear IHC signals. They are denoted as δ_{kl} and expressed in dB. ITD and ILD features are combined into a 2-dimensional binaural feature vectors $\mathbf{o}_{kl} = [\tau_{kl} \ \delta_{kl}]^T$ for each time frame and frequency channel.

Monaural ratemap features r_{kl} are used to model the spectral characteristics of different sound types. They encode a spectro-temporal representation of the auditory-nerve firing rate [15]. Ratemaps are computed individually for each ear signal and frequency channel by smoothing the IHC signal representation with a leaky integrator that has a time constant of 8 ms. The smoothed IHC signal is averaged across all samples within each frame. As the stream segregation process used in this study produces soft masks, corresponding to individual weights for each time-frequency unit, these can directly be applied to the extracted ratemaps. The weighted ratemaps are subsequently used to derive spectral features for each auditory stream, which correlate to perceptual attributes of the corresponding sound source. In this study, 7 attributes are used to classify the identity of the sound source from each stream: spectral centroid [16], spectral spread [17], spectral skewness [18], spectral kurtosis [18], spectral flatness [17], spectral crest [17] and spectral entropy [19]. These attributes are computed for each time frame, yielding the monaural feature vector \mathbf{x}_k . The choice of these features was motivated by their robustness against changes in sound level, in contrast to the level-dependent ratemap features [17].

The proposed machine hearing system utilizes a block-based processing scheme to derive statistics of the spatial sound source characteristics and perform classification of individual auditory streams. Hence, a fixed number of frames K is used to compose non-overlapping *blocks* of auditory features. Throughout this study, $K = 25$ is used which corresponds to a block length of 0.5 s.

2.2. Localization framework

The localization framework has to meet two basic requirements: the ability to estimate the angular direction of a sound source in the entire horizontal plane and the possibility to generate a probabilistic output. Both requirements are necessary for the source segregation framework that will be described below. The localization model proposed in [6, 12] meets both requirements and is thus adopted for this study.

The required mapping from binaural features to azimuth angles is achieved via a statistical framework based on unimodal Gaussian distributions. Individual sets of Gaussian probability density functions (PDFs) are considered for each frequency channel over a discrete set of equidistant azimuth angles $\phi = [-\pi, \pi]$ covering the whole horizontal plane. A set of $M = 360$ Gaussian PDFs per frequency channel is used here, which corresponds to an angular increment of 1° . Hence, the localization model is composed of 360×64 Gaussian PDFs, where each PDF is specified by its mean vector and covariance matrix, represented as a set of model parameters $\theta_l^{(m)}$, $m = 1 \dots, M$. The model parameters are estimated using the 2-dimensional binaural features as described in Sec. 2.1. The training features are computed using anechoic head related impulse responses (HRIR) of the Knowles Electronics Manikin for Acoustic Research (KEMAR) dummy head [20] with white noise stimulus signals. Full covariance matrices were assumed for all models during training.

Evaluating the posterior probability

$$p(\phi^{(m)} | \mathbf{o}_{kl}) \propto \frac{p(\mathbf{o}_{kl} | \theta_l^{(m)})}{\sum_{i=1}^M p(\mathbf{o}_{kl} | \theta_l^{(i)})}$$

for each discrete angular position $\phi^{(m)}$ yields an estimate of the azimuthal sound source direction, computed as the maximum likelihood (ML) solution

$$\tilde{\phi}_{kl} = \arg \max_{\phi^{(m)}} p(\phi^{(m)} | \mathbf{o}_{kl}) \quad (1)$$

for each time-frequency (TF) unit. As Eq. (1) produces an estimate of the source azimuth *relative* to the listeners look direction ψ_k , the latter has to be taken into account explicitly. Therefore, the absolute angular direction of the sound source is computed as

$$\phi_{kl} = ((\tilde{\phi}_{kl} + \psi_k + \pi) \bmod 2\pi) - \pi \quad (2)$$

for each TF unit. For a given set of estimated source positions in a single signal block $\{\phi_{kl}\}$, $k = 1, \dots, K$, $l = 1, \dots, L$, a vector of observations is derived by changing the double element index kl to a single index $n = 1, \dots, N$ with $N = K \cdot L$ over all time and frequency units and stacking the individual observations according to

$$\begin{aligned} \phi &= [\phi_{11}, \dots, \phi_{K1}, \phi_{12}, \dots, \phi_{K2}, \dots, \phi_{KL}]^T, \\ &= [\phi_1, \dots, \phi_N]^T. \end{aligned} \quad (3)$$

2.3. Auditory stream segregation

The auditory stream segregation framework assigns estimates of angular positions to each time-frequency unit of an acquired signal block. This representation serves as the basis for a subsequent clustering step. However, conventional clustering techniques like k -means [21] or Gaussian mixture models (GMMs) [22] might not be suitable for the problem at hand, since the available observations are azimuth angles, originating from a circular probability distribution bounded in $[-\pi, \pi]$. Therefore, an alternative clustering technique is applied here, which is based on a mixture of von Mises distributions [23]. Similar approaches have already been proposed in the context of sound source localization and tracking [24, 25]. In this work, it is applied in the context of auditory stream segregation, by using dummy head HRIRs with a binaural sensor and an auditory feature extraction stage. The PDF of a von Mises distribution is defined as

$$\mathcal{VM}(\phi | \mu, \kappa) = \frac{1}{2\pi I_0(\kappa)} \exp \left\{ \kappa \cos(\phi - \mu) \right\}, \quad (4)$$

where $\phi \in [-\pi, \pi]$ is an angle, μ is the circular mean, κ is the concentration parameter and $I_i(\cdot)$ is the modified i -th order Bessel function. Hence, the PDF of a mixture of von Mises distributions can be derived from Eq. (4) as

$$p(\phi | \boldsymbol{\pi}, \boldsymbol{\mu}, \boldsymbol{\kappa}) = \sum_{c=1}^C \pi_c \mathcal{VM}(\phi | \mu_c, \kappa_c), \quad (5)$$

where $\boldsymbol{\pi} = [\pi_1, \dots, \pi_C]^T$ are the mixture weights satisfying $\sum_{c=1}^C \pi_c = 1$, $\boldsymbol{\mu} = [\mu_1, \dots, \mu_C]^T$ denote the circular means and $\boldsymbol{\kappa} = [\kappa_1, \dots, \kappa_C]^T$ are the concentration parameters corresponding to each of the C mixture components.

The stream segregation process applied in this study is based on the assumption that the number of active sound sources is known *a priori*. Therefore, the number of mixture components C is fixed according to this prior knowledge. For a given set of estimated source positions, the log-likelihood of the PDF introduced in Eq. (5) can be expressed as

$$\mathcal{L}(\phi | \boldsymbol{\pi}, \boldsymbol{\mu}, \boldsymbol{\kappa}) = \sum_{n=1}^N \log \left(\sum_{c=1}^C \pi_c \mathcal{VM}(\phi_n | \mu_c, \kappa_c) \right). \quad (6)$$

The parameters of Eq. (6) are estimated using an expectation maximization (EM) scheme based on the approach presented in [26]. The parameter estimates at each maximization step are given as

$$\mu_c = \text{atan2} \left(\sum_{n=1}^N \gamma_{nc} \sin(\phi_n), \sum_{n=1}^N \gamma_{nc} \cos(\phi_n) \right), \quad (7)$$

$$\kappa_c = A^{-1} \left(\frac{\sum_{n=1}^N \gamma_{nc} \cos(\phi_n - \mu_c)}{\sum_{n=1}^N \gamma_{nc}} \right), \quad (8)$$

$$\pi_c = \frac{1}{N} \sum_{n=1}^N \gamma_{nc}, \quad (9)$$

with

$$A(x) = \frac{I_1(x)}{I_0(x)}. \quad (10)$$

and responsibilities

$$\gamma_{nc} = \frac{\pi_c \mathcal{VM}(\phi_n | \mu_c, \kappa_c)}{\sum_{j=1}^C \pi_j \mathcal{VM}(\phi_n | \mu_j, \kappa_j)} \quad (11)$$

computed during the E-step. Estimating the concentration parameters κ_c requires inverting the function given in Eq. (10). This problem cannot be solved analytically, therefore the inverse function has to be approximated. In this study, the approximation scheme introduced in [27] is applied to estimate the concentration parameters. The EM algorithm utilises Eqs. (7)–(10) to incrementally update the parameter estimates during the optimization process. The initial model parameters are computed using the circular k -means algorithm described in [23].

Following the parameter estimation procedure, the model described in Eq. (5) is used to derive soft masks for all active sound sources, denoted by $c = 1, \dots, C$. The masking coefficients $\beta_{kl}^{(c)}$ for each TF-unit are computed by evaluating the normalized likelihood of the corresponding mixture component, given the estimated azimuth angle:

$$\beta_{kl}^{(c)} = \frac{\mathcal{VM}(\phi_{kl} | \mu_c, \kappa_c)}{\sum_{j=1}^C \mathcal{VM}(\phi_{kl} | \mu_j, \kappa_j)} \quad (12)$$

Note, that the soft-mask estimation assumes a uniform prior over individual mixture components, hence the mixture weights π_c are discarded in Eq. (12). The estimated soft masks are subsequently applied to the extracted ratemap features, yielding an auditory stream $\tilde{r}_{kl}^{(c)} = r_{kl} \cdot \beta_{kl}^{(c)}$ for each source. Individual sets of perceptual attributes $\tilde{\mathbf{x}}_k^{(c)}$ are then derived from these auditory streams as described in Sec. 2.1.

2.4. Source classification

The identities of the sound sources present in the auditory scene are inferred by a classification scheme based on GMMs. Let λ_s represent the characteristics of a sound source in terms of

the monaural auditory features described in Sec. 2.1. Given a set of source models $s = 1, \dots, \mathcal{S}$ and a vector of perceptual attributes $\tilde{\mathbf{x}}_k^{(c)}$, the posterior probability of source model s at frame k can be computed as

$$p(\lambda_s | \tilde{\mathbf{x}}_k^{(c)}) = \frac{p(\tilde{\mathbf{x}}_k^{(c)} | \lambda_s) p(\lambda_s)}{\sum_s p(\tilde{\mathbf{x}}_k^{(c)} | \lambda_s) p(\lambda_s)}. \quad (13)$$

A uniform prior $p(\lambda_s)$ is assumed in this study. As the auditory stream segregation framework described in the previous section utilizes a block-based processing scheme, the posterior probability in Eq. (13) has to be extended accordingly. This is achieved by averaging the frame posteriors across time to produce a posterior probability of source model s given a set of perceptual attributes derived from a block of K frames. The source identity of a block within the c -th auditory stream is the considered to be the source model \hat{s} that maximizes the posterior probability according to

$$\hat{s} = \arg \max_s \frac{1}{K} \sum_{k=1}^K p(\lambda_s | \tilde{\mathbf{x}}_k^{(c)}).$$

2.5. Feedback through rotational head movements

Two different head rotation schemes and their effect on localization and segregation performance are investigated in this study. They are partially adopted from previous work presented in [8]. The case when no rotational head movements are applied serves as a baseline for the performance comparison. The first approach performs random head movements based on the dynamics equation

$$\psi_k = \psi_{k-1} + \frac{\pi}{180} u_k, \quad u_k \sim \mathcal{N}(0, 1).$$

This is a purely feed-forward control strategy, as it uses no information provided by the auditory stream segregation stage.

In contrast, the second approach investigated in this study imposes a feedback loop by turning the head towards the most uncertain of the estimated source positions. The concentration parameters of the mixture of von Mises distributions given in Eq. (5) are used as a measure of uncertainty in this approach, yielding the index of the most uncertain source position as

$$\tilde{c} = \arg \min_c \kappa_c.$$

Feedback is subsequently initiated using the dynamics equation

$$\psi_k = \psi_{k-1} + \alpha(\mu_{\tilde{c}} - \psi_{k-1}), \quad (14)$$

where α is a fixed gain factor set to $\alpha = 5$ throughout all experiments. For both proposed approaches, possible head rotations were restricted to the range $[-80^\circ, 80^\circ]$ relative to the initial look direction which was fixed at 90° .

3. Evaluation

3.1. Sound database

A collection of speech and non-speech sounds was created using the GRID corpus [28] and a publicly available sound database¹. Five different classes of sounds with diverse spectro-temporal complexity were selected: *female speech*, *alarm/siren*, *dog barking*, *car engine* and *piano*. Silence periods in all sound files were manually labeled.

¹<https://www.freesound.org/>

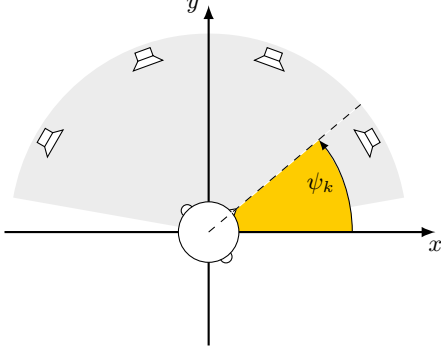


Figure 1: Layout of the acoustic scene used during the evaluation. Sound sources can be positioned at 30° , 70° , 110° and 150° . The gray area indicates the range of possible head rotations.

3.2. Experimental setup

The proposed framework was evaluated in simulated acoustic scenes, which were generated using anechoic HRIRs [20]. Three different scenarios with either 2, 3 or 4 simultaneously active sound sources were considered. The sources were positioned randomly at fixed azimuth angles relative to the dummy head. An overview of the general acoustic scene configuration used for the evaluation is depicted in Fig. 1. It is worth mentioning that, even though the sources were all placed within the frontal hemisphere, the system had no prior knowledge about the azimuthal positions. This was ensured by initializing the stream segregation stage with uniform circular distributions.

The acquired sound database was partitioned into 10 folds of training and test sets, allowing cross-validation of the dataset in all evaluation scenarios. Monaural feature vectors were extracted for each sound class from the training files and used to train the GMM-based classifiers described in Sec. 2.4. All GMMs were trained using EM iterations with a fixed number of 16 mixture components and full covariance matrices. Silence periods were excluded from the audio files during training.

During each cross-validation step, 30 simulations with a fixed duration of 3 s each were conducted for testing. The specific setup of each simulation was composed of randomly chosen sounds from the test set. Localization and classification performance were measured by computing the block-wise, cumulative circular root mean square error (RMSE) and classification error rate, respectively.

3.3. Results and discussion

The results obtained in all evaluation scenarios are summarized in Tab. 1. The feedback strategy introduced in Eq. (14) outperforms both the static case and the feed-forward control scheme based on random head movements in all evaluated scenarios. Furthermore, random head movements yield no significant improvements with respect to the baseline throughout all conducted experiments. This effect is similar to the results described in [8], where it was shown that control strategies based on a feed-forward paradigm are not as beneficial for localization performance as closed-loop feedback control.

The results obtained in this work indicate that classification performance of the proposed machine hearing system is highly dependent on localization accuracy. An increasing number of simultaneously active sound sources results in a severe drop in

Table 1: This table summarizes the averaged localization and classification performance achieved in all conducted experiments for different head rotation strategies. The localization error is given as cumulative circular RMSE in degrees, whereas classification error is depicted as classification error rate in percent. The best performances achieved in each of the scenarios are depicted in bold font.

Head rotation	Localization error	Classification error
Scenario 1: 2 active sound sources		
None	30.12	31.67
Random	28.91	31.07
Feedback	20.91	23.33
Scenario 2: 3 active sound sources		
None	64.52	67.75
Random	62.67	67.78
Feedback	61.82	63.19
Scenario 3: 4 active sound sources		
None	78.94	77.96
Random	78.97	78.35
Feedback	70.45	74.79

localization performance, which subsequently also reduces the stream segregation abilities of the system. This effect is caused by the rather basic localization framework used in this study, which is based on Gaussian PDFs. A more sophisticated model would most certainly yield in better azimuth estimations, thus providing more accurate features to the clustering stage of the stream segregation framework.

4. Conclusions

This study presented an active machine hearing system for auditory stream segregation in multi-source scenarios. The proposed system is based on a framework for joint localization and stream segregation, using a probabilistic clustering scheme to assign individual TF units to azimuthal sound source positions. The framework is termed *active*, because it is able to dynamically assess the auditory scene by conducting head movements. Experimental results have indicated, that rotational head movements based on a closed-loop feedback control scheme increase localization and stream segregation performance. This was shown in simulated acoustic environments using a combined stream segregation and classification system to infer the identities of different speech and non-speech sounds in multi-source scenarios.

Future developments will focus on improving the localization framework used in this study, e.g. by incorporating GMMs or DNNs for predicting azimuth angles for each TF unit. Additionally, different head rotation strategies may yield further improvements of auditory stream segregation performance. In this context, it will be especially interesting to investigate head movements conducted by human listeners in multi-source scenarios and apply according strategies to the proposed computational system.

5. Acknowledgements

This research has been supported by EU FET grant TWO!EARS, ICT-618075.

6. References

- [1] A. S. Bregman, *Auditory Scene Analysis: The Perceptual Organization of Sound*. Cambridge, MA: MIT Press, 1990.
- [2] J. Blauert, *Spatial Hearing: The Psychophysics of Human Sound Localization*. Cambridge, MA: MIT Press, 1999.
- [3] D. Wang and G. J. Brown, *Computational Auditory Scene Analysis: Principles, Algorithms, and Applications*. Wiley-IEEE Press, 2006.
- [4] M. I. Mandel, R. J. Weiss, and D. P. W. Ellis, "Model-based expectation-maximization source separation and localization," *Trans. Audio, Speech and Lang. Proc.*, vol. 18, no. 2, pp. 382–394, 2010.
- [5] A. Deleforge, F. Forbes, and R. Horaud, "Variational EM for binaural sound-source separation and localization," in *IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)*, 2013, pp. 76–80.
- [6] N. Ma, T. May, H. Wierstorf, and G. J. Brown, "A machine-hearing system exploiting head movements for binaural sound localisation in reverberant conditions," in *IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)*, 2015, pp. 2699–2703.
- [7] N. Ma, G. J. Brown, and J. A. Gonzalez, "Exploiting deep neural networks and head movements for binaural localisation of multiple speakers in reverberant conditions," in *INTERSPEECH 2015, 16th Annual Conference of the International Speech Communication Association, Dresden, Germany, September 6-10, 2015*, pp. 3066–3070.
- [8] C. Schymura, F. Winter, D. Kolossa, and S. Spors, "Binaural sound source localisation and tracking using a dynamic spherical head model," in *INTERSPEECH 2015, 16th Annual Conference of the International Speech Communication Association, Dresden, Germany, September 6-10, 2015*, pp. 165–169.
- [9] H. Wallach, "The role of head movements and vestibular and visual cues in sound localization," *Journal of Experimental Psychology*, vol. 27, no. 4, 1940.
- [10] E. Hoffmann, D. Kolossa, and R. Orglmeister, *Independent Component Analysis and Signal Separation: 7th International Conference, ICA 2007, London, UK, September 9-12, 2007. Proceedings*. Berlin, Heidelberg: Springer Berlin Heidelberg, 2007, ch. A Batch Algorithm for Blind Source Separation of Acoustic Signals Using ICA and Time-Frequency Masking, pp. 480–487.
- [11] K. Rahbar and J. P. Reilly, "A frequency domain method for blind source separation of convolutive audio mixtures," *IEEE Transactions on Speech and Audio Processing*, vol. 13, no. 5, pp. 832–844, Sept 2005.
- [12] T. May, S. van de Par, and A. Kohlrausch, "A Probabilistic Model for Robust Localization Based on a Binaural Auditory Front-End," *Audio, Speech, and Language Processing, IEEE Transactions on*, vol. 19, no. 1, pp. 1–13, Jan. 2011.
- [13] R. Decorsière, T. May, C. Kim, and H. Wierstorf, "Two!Ears Auditory Front-End 0.8," 2015. [Online]. Available: <http://dx.doi.org/10.5281/zenodo.13788>
- [14] T. Dau, D. Püschel, and A. Kohlrausch, "A quantitative model of the "effective" signal processing in the auditory system: I. model structure," *Journal of the Acoustical Society of America*, vol. 99, pp. 3615–3622, 1996.
- [15] G. J. Brown and M. Cooke, "Computational auditory scene analysis," *Computer Speech & Language*, vol. 8, no. 4, pp. 297–336, 1994.
- [16] G. Tzanetakis and P. Cook, "Musical genre classification of audio signals," *IEEE Transactions on Speech and Audio Processing*, vol. 10, no. 5, pp. 293–302, Jul 2002.
- [17] G. Peeters, B. Giordano, P. Susini, N. Misdariis, and S. McAdams, "The timbre toolbox: extracting audio descriptors from musical signals," *Journal of the Acoustical Society of America*, vol. 130, no. 5, pp. 2902–2916, 2011.
- [18] A. Lerch, *An Introduction to Audio Content Analysis: Applications in Signal Processing and Music Informatics*, 1st ed. Wiley-IEEE Press, 2012.
- [19] H. Misra, S. Ikbal, H. Bourlard, and H. Hermansky, "Spectral entropy based feature for robust ASR," in *IEEE International Conference on Acoustics, Speech, and Signal Processing, 2004. Proceedings. (ICASSP '04)*, vol. 1, May 2004, pp. I–193–6 vol.1.
- [20] H. Wierstorf, M. Geier, and S. Spors, "A Free Database of Head Related Impulse Response Measurements in the Horizontal Plane with Multiple Distances," in *Proc. of 130th Aud. Eng. Soc. Conv.*, London, UK, 2011.
- [21] J. B. MacQueen, "Some methods for classification and analysis of multivariate observations," in *In 5-th Berkeley Symposium on Mathematical Statistics and Probability*, 1967, pp. 281–297.
- [22] A. Dempster, N. Laird, and D. Rubin, "Maximum likelihood from incomplete data via the EM algorithm," *J. Royal Statistical Society, Series B*, vol. 39, no. 1, pp. 1–38, 1977.
- [23] A. Banerjee, I. S. Dhillon, J. Ghosh, and S. Sra, "Clustering on the Unit Hypersphere Using Von Mises-Fisher Distributions," *J. Mach. Learn. Res.*, vol. 6, pp. 1345–1382, Dec. 2005.
- [24] J. Traa and P. Smaragdis, "Multiple speaker tracking with the factorial von mises-fisher filter," in *2014 IEEE International Workshop on Machine Learning for Signal Processing (MLSP)*, Sept 2014, pp. 1–6.
- [25] I. Markovic and I. Petrovic, "Bearing-only tracking with a mixture of von mises distributions," in *2012 IEEE/RSJ International Conference on Intelligent Robots and Systems*, Oct 2012, pp. 707–712.
- [26] W.-L. Hung, S.-J. Chang-Chien, and M.-S. Yang, "Self-updating clustering algorithm for estimating the parameters in mixtures of von Mises distributions," *Journal of Applied Statistics*, vol. 39, no. 10, pp. 2259–2274, 2012.
- [27] D. Best and N. Fisher, "The bias of the maximum likelihood estimators of the von Mises-Fisher concentration parameters," *Communications in Statistics - Simulation and Computation*, vol. 10, no. 5, pp. 493–502, 1981.
- [28] M. Cooke, J. Barker, S. Cunningham, and X. Shao, "An audio-visual corpus for speech perception and automatic speech recognition," *The Journal of the Acoustical Society of America*, vol. 120, no. 5, pp. 2421–2424, 2006.